Fires and Air Past,

by M. Talat Odman, Yongtao Hu, Fernando Garcia-Menendez, Aika Y. Davis, Michael E. Chang, and Armistead G. Russell

M. Talat Odman is a principal research engineer, **Yongtao Hu** is a senior research scientist, **Aika Y. Davis** is a graduate research assistant, and **Armistead (Ted) G. Russell** is the Howard T. Tellepsen Chair and Regents' Professor, all with the School of Civil and Environmental Engineering at Georgia Institute of Technology; **Fernando Garcia-Menendez** is a postdoctoral associate with the Center for Global Change Science at Massachusetts Institute of Technology; and **Michael E. Chang** is the deputy director of the Brook Byers Institute for Sustainable Systems at Georgia Institute of Technology. E-mail: M. Talat Odman, odman@gatech.edu.

A look at the evolution of methods for forecasting wildfire and prescribed burn impacts on air quality.

Wildfires threaten our lives not only through their destructive power, but also with their significant impact on air quality.[1] Local- and regional-scale impacts of fires on atmospheric composition are apparent in the concentrations of trace gases and aerosols, including carbon monoxide, nitrogen oxides, ozone, black carbon, and particulate matter. Emissions from fires impair visibility and adversely affect public health. Poor visibility has led to fatal highway accidents, and several epidemiological analyses have identified statistically significant associations between fire-related smoke and respiratory- and asthma-related hospital admissions.[2]

In the United States, a considerable fraction of air pollution can be attributed to fire-related emissions. At present, wildfires largely drive the variability in summertime organic carbon aerosol concentrations in the western United States.[3] Though less common, emissions from wildfires in the eastern United States, such as the Florida-Georgia fires of 2007 and North Carolina peat fires of 2008, can endanger the lives of larger populations in urban areas. In addition, wildfire activity may strengthen under a changing climate. Studies suggest that a warmer and drier climate increase the area burned by wildfires and their severity.[4-6] The response of plants and vegetation to climate is not necessarily considered in these studies, but fuel loads may also increase in the future leading to more intense fires with larger emissions. Considerable increases to organic and elemental carbon aerosol concentrations can be expected to occur by mid-century as fire-related emissions intensify.[7]

Controlled fires, also known as prescribed burns, can also be a major contributor to air pollution.[8]

Quality Forecasts Present, and Future

Prescribed burns are frequently used as a land-management strategy and have proven to be effective toward accomplishing different objectives, such as habitat restoration, wildfire prevention, endangered species protection, site preparation for seeding and planting, and disease control. In the past decade, more than 30% of the area burned by fires within the contiguous United States corresponded to prescribed burns.[9]

In the southeastern United States, where prescribed burning is a preferred method of land management, more than 8 million acres of land are treated by fire every year,[10] and this amount could easily double if there were no limiting air quality concerns.[11] Source apportionment modeling of fine particulate matter ($PM_{2.5}$) measurements from 24 Speciation Trend Network sites in the southeastern United States suggests that prescribed burning may be contributing more than 30% of the annual $PM_{2.5}$ mass.[12] Recent studies show that prescribed burning can significantly impact air quality in neighboring urban communities, contributing significantly not just to $PM_{2.5}$, but ozone as well.[13-15] For example, on February 28, 2007, due to a prescribed burn, 1-hr $PM_{2.5}$ concentrations at several monitors in Atlanta, GA, reached 145 µg m^{-3} (the NAAQS for 24-hr $PM_{2.5}$ is 35 µg m^{-3}), increasing by more than 100 µg m^{-3} in just two hours. In addition, 1-hr average ozone concentrations increased markedly from 63 parts per billion (ppb) to 95 ppb at one of the monitors.[16]

The concern over fires in air quality planning efforts is expected to grow as air quality standards become more stringent and emissions from other anthropogenic sources are better controlled. Because prescribed burn impacts on air quality can be exacerbated or diluted, depending on ambient meteorological conditions and interactions with other emissions in and around large metropolitan areas, integrating air quality forecasting in prescribed burn management can avoid creating serious air

Acknowledgment:
This article was made possible by grants from the Joint Fire Science Program (12-3-01-60), NASA (NNX11AI55G), and U.S. Environmental Protection Agency (RD83521701), and a contract with the Georgia Department of Natural Resources (773-120170). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the supporting agencies. Reference herein to any specific commercial products, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement or recommendation by the authors.

Modeling suggests that prescribed burning may be contributing more than 30% of the annual $PM_{2.5}$ mass in the southeastern United States.

pollution incidents. Further, a dynamic air quality management approach based on forecasting would not only mitigate the undesirable impacts of fire emissions, but may also increase burning capacity by allowing additional emissions when conditions are favorable. However, such an approach would require more accurate predictive tools for forecasting fire emissions and their air quality impacts.

Models for Forecasting

Weather forecasting is the first step in predicting the impacts of fires. Since numerical weather prediction models are relatively well developed, we will not discuss them here. Using the weather forecast simply as an input to fire impact simulations is a common approach and is appropriate, as long as the fire does not interfere with the weather. However, some fire plumes are known to create their own local weather. Models currently under development to capture the feedback of fire plumes on weather[17] should be considered for fire impact forecasting in the future.

Estimation of fire emissions usually consists of approximating the amounts of different types of fuels consumed and multiplying them with emission factors derived from field studies or laboratory experiments measuring the amounts of various pollutants emitted per unit mass of consumed fuels. The fuel consumption estimation typically begins by characterizing the fuel loads. For wildfires, fuel loads can be obtained from National Fire Danger Rating System (NFDRS) or similar maps. For prescribed burns, fuels can be surveyed and matched with the closest depiction in a catalog where each photograph has corresponding fuel loads.[18] A consumption model can then be used to calculate the fractions of fuels that would be consumed under predicted fire conditions. Several fire emission modeling tools are available through the BlueSky framework,[19] including the consumption model CONSUME,[20] which considers fuel loads, fuel moistures, and intensity of the fire to calculate fuel consumptions. BlueSky also compiles emission factors from various sources.

A variety of models have been developed and used for predicting the dispersion and transport of fire-related emissions. Simple Gaussian plume models have been developed to assist land managers in planning prescribed burns, such as VSMOKE and the Simple Approach Smoke Estimation Model.[21,22] Puff models, which simulate fire emissions as a series of continuously emitted parcels, can be used to model dispersion under space- and time-varying meteorological fields over detailed terrain. Calpuff, a widely used puff model, has been applied to simulate the transport of fire plumes.[23,24] The Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT) is a component of the Smoke Forecasting System used by the U.S. National Weather Service to produce daily smoke forecasts.[25] Other Lagrangian particle models, such as FLEXPART, have been used to simulate biomass burning plumes.[26,27] Daysmoke, another member of the Lagrangian family, has been specifically developed for modeling the dispersion and transport of prescribed burn plumes.[28]

All these models lack the chemical detail that would be needed to predict the air quality impacts of fires, particularly the formation of secondary pollutants such as ozone and a potentially large fraction of organic aerosols. Some do not include any representation of chemistry (e.g., VSMOKE, Daysmoke) and simply treat the fire plume as a mixture of inert gases or particles. Others may have characterizations of chemical reactions in the atmosphere, but generally in a very simplistic way (e.g., Calpuff and HYSPLIT). This is not surprising given the fact that these models are used in forecasts mainly concerned with primary smoke impacts and not secondary air pollution or the interactions with emissions from other sources over large geographic regions.

An alternative approach to simulating the transport and transformation of fire emissions is to use Eulerian chemical transport models (CTMs). These models use weather forecasts, emissions estimates, and mathematical representations of atmospheric processes to predict the evolution of pollutant concentrations over large geographic regions. Today, CTMs are extensively applied in North America and Europe to design environmental policy, generate air quality forecasts, and study atmospheric physics and chemistry.[29] In contrast to Lagrangian dispersion models, Eulerian CTMs include state-of-the science representations of chemical and physical atmospheric transformations.

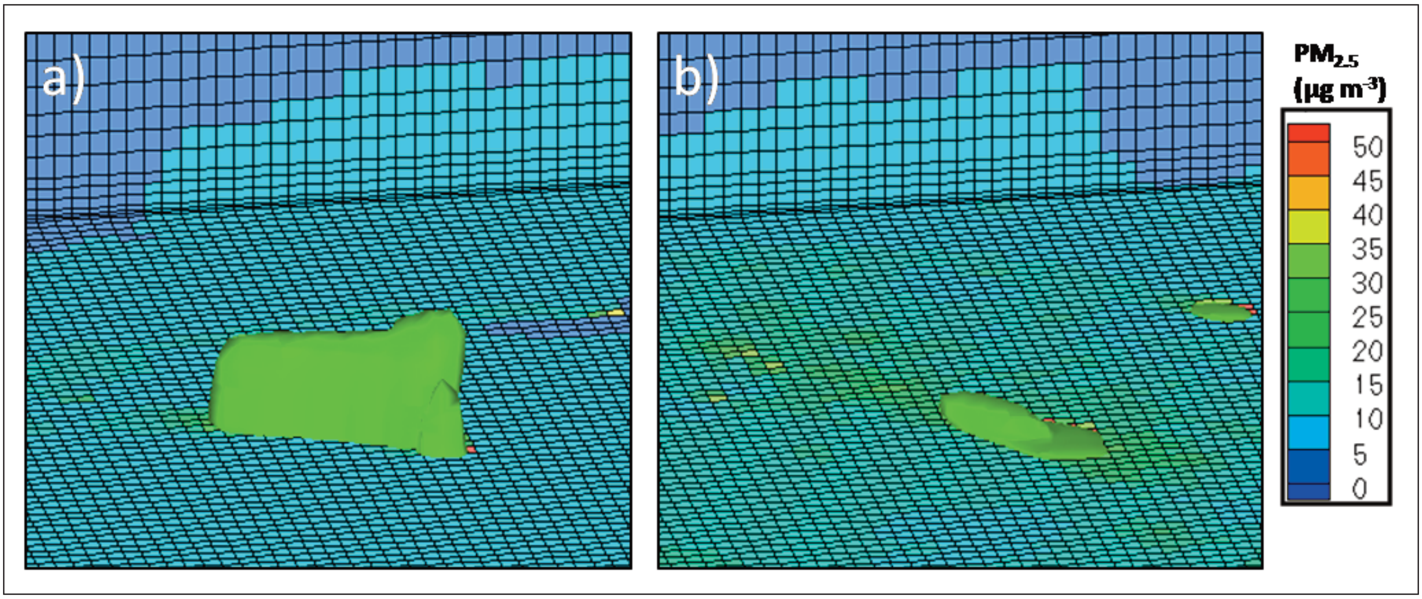

Figure 1. Prescribed burn smoke plume, shown as a three-dimensional iso-surface defined by $PM_{2.5}$ concentrations equal to 35 µg m^{-3}, simulated by CMAQ using vertical distribution profiles that allocate flaming emissions mostly (a) within the PBL and (b) into the free troposphere. Ground-level and lateral boundary $PM_{2.5}$ concentrations are also shown.

Previous applications of Eulerian CTMs for predicting the impacts of wildland fires have achieved greater understanding of the atmospheric processes affecting fire-related emissions.[30,31] However, there are limitations associated with the current generation of models because of their relatively coarse resolution. Eulerian CTMs operate by dividing an atmospheric domain into a number of discrete cells and simulating atmospheric processes for every cell. Computational requirements typically restrict grid resolution in regional-scale applications to a few kilometers. Emissions are immediately diluted upon injection into a grid cell, losing potentially important information about the subgrid-scale structure of a plume. As pollutants are dispersed, coarse grid resolution causes artificial diffusion by uniformly mixing pollutants within each cell. This leads to a loss of accuracy, especially in the modeling of nonlinear chemical transformations. Processes occurring at scales smaller than those captured by the grid resolution must be parameterized in CTMs. Some CTMs offer subgrid-scale plume treatments for emissions from industrial stacks, but not for fire-related emissions.

The vertical distribution of fire emissions is an important component of air quality simulations centered on smoke transport. Theoretical or empirical plume rise representations, with varying levels of complexity, are often used to approximate vertical plume structures. The fraction of fire emissions penetrating into the free troposphere is a key model parameter. Pollutant concentrations predicted by CTMs are highly sensitive to the altitude at which fire emissions are injected relative to the planetary boundary layer (PBL).[32] For instance, Figure 1 shows a prescribed burn smoke plume simulated by the Community Multiscale Air Quality (CMAQ) model,[33] an Eulerian CTM, using different vertical distribution profiles. The vertical profile that retains flaming-stage fire emissions within the PBL (Figure 1a) produces a concentrated smoke plume. In contrast, allocating the majority of fire emissions into the free troposphere leads to a weaker and highly diffused plume (Figure 1b). The air quality impacts predicted by the model at downwind receptors in each case differ significantly.

Air quality forecasting requires emission forecasts as one of its inputs. One approach to projecting fire emissions to the future has been to develop a typical fire emissions inventory by averaging several years' fires.[34] The rationale is that since the locations, frequencies, and strengths of future fires cannot be predicted accurately, a typical year's fires would be a reasonable representation of future years' fires. In this manner, the probability of introducing large uncertainties by using a single year's high or low fire activity is reduced. In the past, this approach has been used by the U.S. Environmental Protection Agency (EPA) and regional planning organizations (RPOs) for regulatory purposes, and adopted by operational air quality forecasting systems such as Hi-Res.[35]

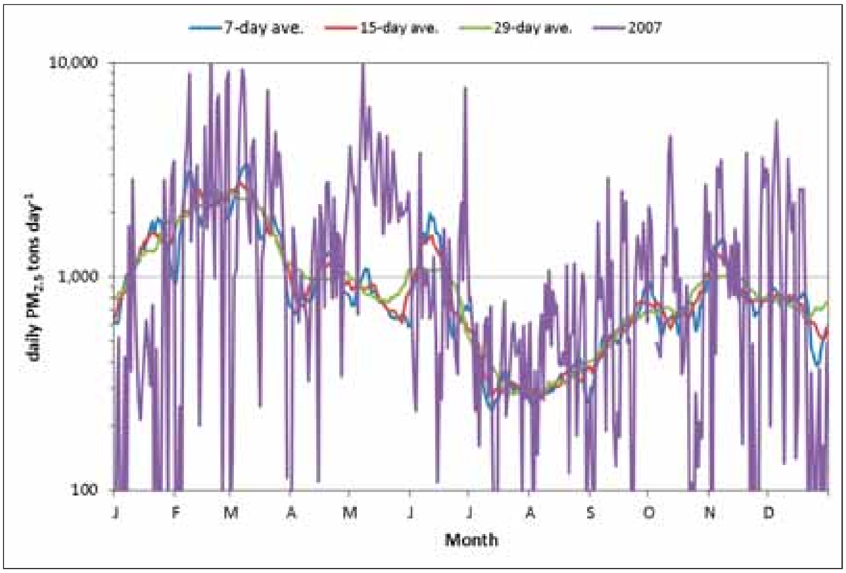

Figure 2. Typical fire emissions for Southeast United States generated by Fire Averaging Tool using 7-, 15-, and 29-day averaging with the 2003–2009 inventories and actual fire emissions from the 2007 inventory.[34]

As an example of the typical year approach, the Fire Averaging Tool (FAT) developed by EPA generates day-specific fire emissions for each county by taking the rolling average over a specified period of daily fire emissions in that county for the years being included in the average. For example, if the selected averaging period is 29 days (+/- 14 days) and the years included are 2003–2009, then for July 15 the tool averages all the fires in that county from July 1 to July 29 for 2003–2009. Figure 2 illustrates how a 29-day averaging period leads to emissions smoother than those produced by 15- or 7-day averaging periods and how the use of multi-year data greatly reduced day-to-day variability compared to the actual 2007 point fire inventory.[34] FAT also smoothed the fires spatially by averaging multiple years of fire emissions over each county. All these effects of averaging ultimately lead to a typical year with more frequent but less intense fires over larger spans.

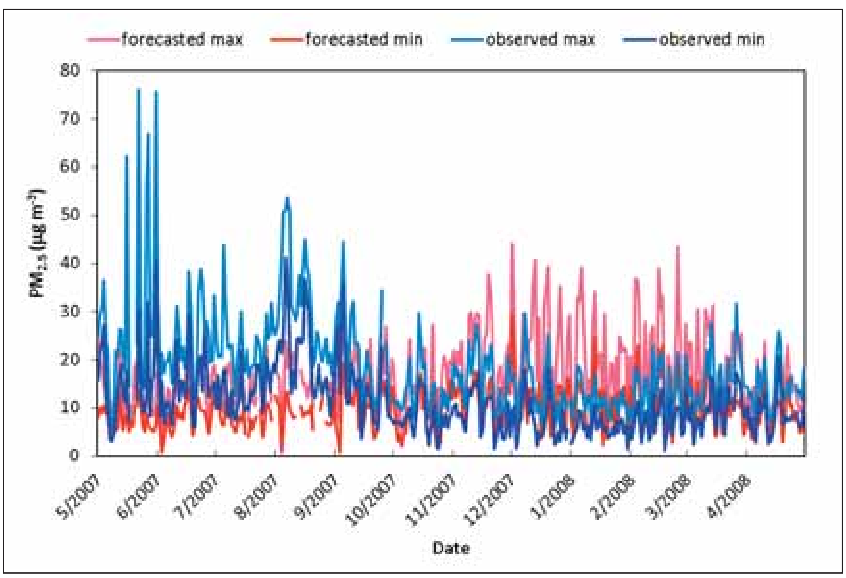

Figure 3. $PM_{2.5}$ forecasts and observations in Atlanta, GA, between May 2007 and April 2008.

Note: Max and min represent the maximum and minimum observed or forecasted daily average $PM_{2.5}$ concentrations at the monitoring sites in the area.

The Hi-Res operational air quality forecasting system[35,36] used a typical year inventory developed by averaging fire emissions of years 1999–2003 in its 2007–2008 forecasting.[37] Figure 3 shows how using typical fire emissions in the Hi-Res system caused forecasted $PM_{2.5}$ concentrations to deviate from observations in Atlanta. Due to CMAQ's tendency to underestimate organic carbon concentrations, the forecasted summertime $PM_{2.5}$ concentrations were low compared to the observations. In May 2007, the forecasts were extremely low compared to observations, having missed several hits by smoke plumes from the Florida-Georgia fires absent in the typical inventory. During winter, the frequency of fires was larger in the typical inventory than in reality, leading to an overprediction of $PM_{2.5}$ concentrations on most days. These results reveal that it is not appropriate for an operational air quality forecasting system to rely on typical year fire emissions averaged from historical multi-year data.

Satellite Products

In recent years, satellites have been used for fire detection, and satellite fire products allow for derivation of biomass fire emissions. The Satellite Mapping Automated Reanalysis Tool for Fire Incident Reconciliation (SMARTFIRE) system[38] provides a satellite-based fire emissions inventory. SMARTFIRE uses the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System fire location information combined with the Fuel Characteristic Classification System and CONSUME to estimate fire emissions from wildfires and prescribed burns on a daily basis. The SMARTFIRE emissions inventory is now being widely used by the EPA and RPOs for their regulatory modeling efforts. However, for reasons stated above, such historical fire emissions inventories are inadequate for operational air quality forecasting.

There are also near-real-time biomass burning emissions products derived from satellites such as the Fire Inventory of NCAR (FINN)[39] and Global Biomass Burning Emission Product from geostationary satellites (GBBEP-Geo).[40] FINN uses active fire detections from the Moderate Resolution Imaging Spectroradiometer's (MODIS) Thermal Anomalies Product and the MODIS Collection 5 Land Cover Type product, together with estimated fuel consumptions and emission factors to obtain daily open burning emissions estimates at approximately 1-km spatial resolution.

GBBEP-Geo produces hourly biomass burning emissions using satellite-derived fire radiative power (FRP) for individual fire pixels at approximately 4-km resolution. FRP is retrieved using the wildfire automated biomass burning algorithm from a network of multiple geostationary satellites, including NOAA's two Geostationary Operational Environmental Satellites (GOES), the European Meteosat second-generation satellites, and the Multifunctional Transport Satellite operated by the Japan Meteorological Agency. FRP is a function of area burned, fuel loading, and combustion efficiency that provides a means to directly derive biomass consumption from satellite data.[41]

Both the FINN and GBBEP-Geo products could potentially be used in operational air quality forecasting to track emissions from large wildfires and predict their near-future trends. In addition, aerosol optical depth (AOD) available in near-real-time from MODIS and GOES, as well as carbon monoxide concentrations from Measurements of Pollution in the Troposphere (MOPITT) can be assimilated into modeled concentration fields to more accurately forecast fire impacts.

A recent comparison of satellite-based biomass burning emissions products revealed inconsistencies between the different methods used with various satellite instruments and large discrepancies in the emissions estimates.[42] Whenever possible, satellite-based biomass burning emissions products should be calibrated using data from alternative sources. For example, SMARTFIRE uses ground-based incident reports to reconcile its satellite fire detections.

FRP used in GBBEP-Geo as a proxy for the rate of biomass consumption is derived from limited experiments.[43] Its relation to biomass consumption needs to be more intensively calibrated.[44] Satellite products also can be evaluated using various ground-based emission inventories such as the U.S. National Wildfire Emission Inventory.[45]

Aircraft measurements taken in fire plumes can be used as another source of independent data to calibrate satellite retrievals and reconcile with ground-based emissions data. To illustrate this concept, emissions from a prescribed burn were estimated using both ground-based information and satellite observations. The ground-based information was fed into a series of models for fuel loads, fuel consumptions, and emissions, as in the BlueSky framework. The satellite-based emissions estimate was derived from GBBEP.[45] In this case, the ground-based estimate is significantly larger than the satellite-based emissions estimate (Figure 4a). The temporal profiles were also significantly different: satellite-based emissions ramped up, reached their peak toward the middle of the burn, and then tapered off, while the ground-based emissions were more level during the flaming phase followed by two hours of smoldering.

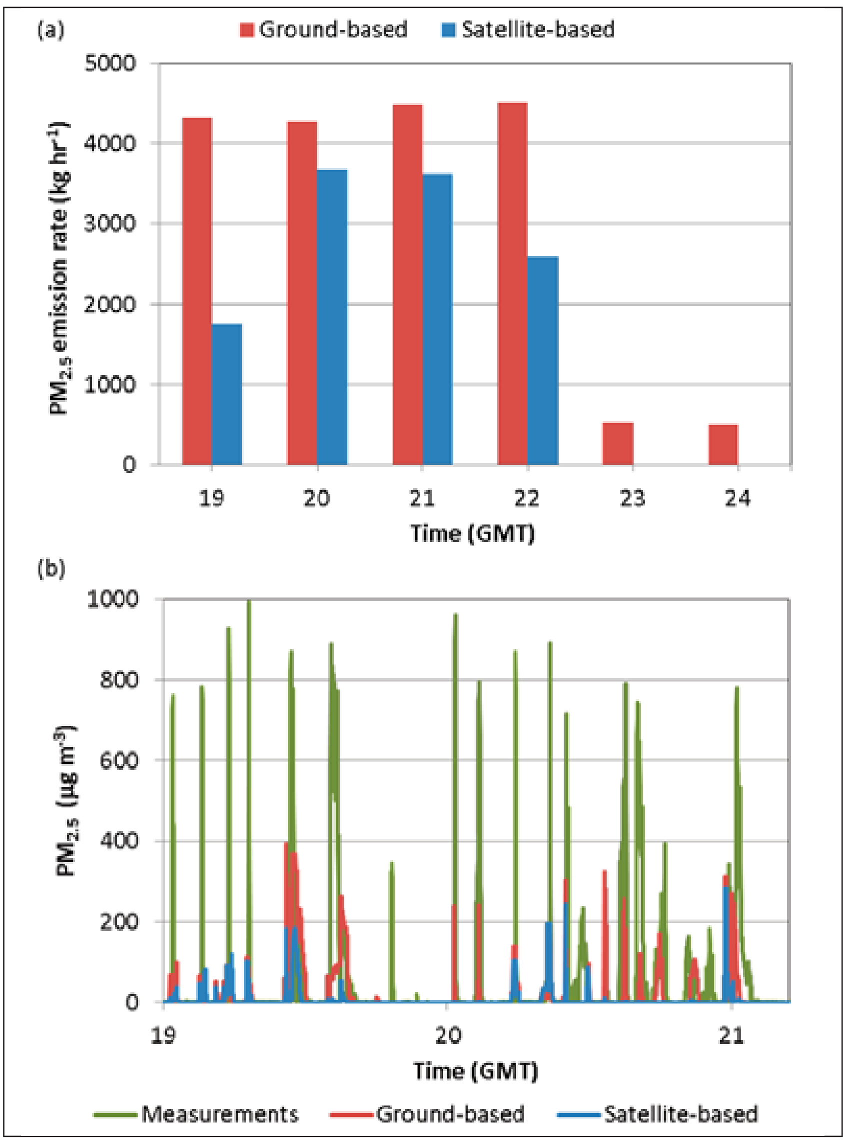

Figure 4. (a) Ground- and satellite-based emission estimates for a prescribed burn conducted on November 17, 2009, near Santa Barbara, CA, over 80 ha of land covered with chaparral; (b) downwind $PM_{2.5}$ concentrations predicted by using those estimates in Daysmoke and derived from light scattering measurements by aircraft.

The burn was then simulated using both sets of emission estimates and meteorological parameters predicted by a numerical weather prediction model as inputs to the Daysmoke plume rise and dispersion model. During this burn, an aircraft tracked the smoke plume and measured carbon dioxide and light scattering along with meteorological parameters.[46] Concentrations of smoke predicted by using both ground- and satellite-based emissions estimates were compared along the trajectory of the aircraft to corresponding measurements. This type of comparison is one of the most challenging evaluations for a model where the predictions are paired with measurements both in space and time. While the concentration peaks were generally synchronized, there were large differences between the magnitudes of modeled and measured maxima (Figure 4b).

Since the differences from the measurements are larger than the differences between the two sets of model-predicted concentrations, it is not possible to determine which emissions estimate is more accurate for this case. A comparison of predicted winds to those measured by the aircraft revealed differences both in speed and direction that could easily lead Daysmoke to divert the smoke plume from its observed trajectory. Since modeled concentrations can be very sensitive to uncertainties in predicted wind fields, a less strict pairing of predicted and measured concentrations, for example one with pairing in time but not in space, is recommended.

Toward a Better Fire Impact Forecasting System

Once properly calibrated, near-real-time biomass burning emissions products derived from satellites may be beneficial for air quality forecasting. For example, when a large wildfire is detected by satellite, its emissions can be input to the next forecast cycle and Eulerian CTMs with sufficiently high resolution can track those emissions. However, these satellite products are not as useful with prescribed burns for several reasons. First, prescribed burns are of short duration; they may be ignited and extinguished between satellite scans and go completely undetected. Second, their radiative power is much weaker than large wildfires, making them more difficult to detect and estimating their emissions more prone to uncertainties. Finally, it is difficult to incorporate prescribed burns detected by satellites into the forecast because of their short duration. However, there are some applications like the forecasting of the extremely dangerous superfog[47] where the tracking of prescribed burn emissions overnight would be beneficial.

While the use of satellite products is not a current option for forecasting the air quality impacts of prescribed burns, the use of typical fire emissions can lead to poor air quality forecasts, as shown above. What is needed is a better way of estimating prescribed burn emissions. Since weather plays an important role in the decision of the prescribed burner, weather forecasts can be used in predicting prescribed burning activity, at least on a burn/no-burn decision level. One can also assume that if the conditions are perfect, there would be more acres burned. Burners are primarily concerned with the conditions of the fuel and soil: the fuel must be dry enough to burn, but the soil should be damp enough to protect trees from the burn. Wind speed, wind direction, and atmospheric stability are other factors that would be considered to conduct the burn safely, effectively, and without hitting any sensitive targets with smoke. Precipitation, temperature, humidity, and winds are the primary weather parameters determining the fuel and soil moistures. These can be combined with other factors, such as the fuel/soil type, to predict fuel/soil moisture. Alternatively, simple rule-based decision trees can be used to determine whether the prescribed burner would attempt to burn or not. We will illustrate this with the following example.

Forecasting Prescribed Burn Emissions

Figure 5 shows the acreage of the burns permitted in northern Bryan County, GA, for each day in March 2010. Bryan County is home to Ft. Stewart, a large training base for the U.S. Army. Also shown in Figure 5 is the daily precipitation measured at Ft. Stewart. In Georgia, burning permits are requested and granted by telephone or online, typically on the morning of the burn. Therefore, the area permitted to be burned is a good indication of the intent for burning on that day. Note that no burns were attempted on a rainy day or the following day. The large rain event on March 11 (2 inches) is followed by three days of inactivity. Burn/no-burn decisions are made based on the rain forecast, not actual precipitation. On days with no precipitation, a high probability of rain in the forecast could have deterred the prescribed burners. For example, March 26 could be one of those days. However, it is more likely that high winds in the forecast influenced the decision against the burns as the maximum wind speed recorded at Ft. Stewart was 22 mph on that day. Another deterrent may have been a westerly wind forecast, which could have put highly populated areas to the east in Chatham County and Savannah at risk of smoke.

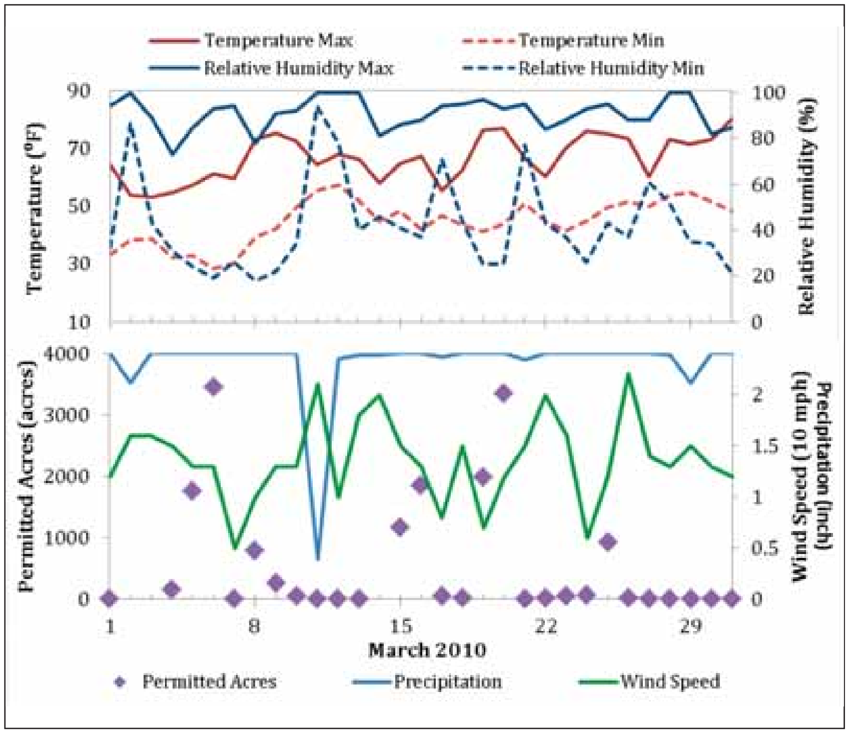

Figure 5. Daily maximum/minimum temperatures and relative humidities, maximum wind speed, and 1-hr accumulated precipitation (top to bottom) recorded at Ft. Steward and total areas of land permitted for prescribed burning in northern Bryan County, GA, in March 2010.

The next challenge in forecasting prescribed burn emissions is to predict the location and size of the burns. One approach is to keep an inventory of the managed lands, their frequency of treatment, and the last time they were burned. The Georgia Forestry Commission (GFC) electronically tracks all

A recent comparison of satellite-based biomass burning emissions products revealed inconsistencies between the different methods used with various satellite instruments and large discrepancies in the emissions estimates.

burn permits issued since 2005. Databases such as this one can be mined to identify all burners, analyze their burning patterns, and identify their burning frequency and last burning year. Burners whose burning cycles intersect with the current year can be put in a "likely burners" list. For example, a plot on a three-year rotation that was last treated three years ago is likely to be burned this year. At the start of the burning season, it can be assumed that all likely burners would burn over a typical number of days with favorable weather conditions.

The burning season in Georgia is limited to October 1 through April 30 owing to a burning ban during the ozone season (May 1 through September 30). Suppose, on average, there are 20 days favorable for burning in a season. Then, for forecasting purposes, a randomly selected 1/20 of the likely burners could be assumed to be burning on the first occurrence of favorable weather conditions. As the season progresses, the list of likely burners can be updated by dropping those who have already burned and adjusting the number of average burning days based on the days remaining in the season. If the season has been extremely wet thus far, it can be assumed that a larger than average fraction of the burners would be burning on the next chance they get. The GFC database also describes the purpose of the burn. Burns may be conducted early or later in the season, depending on the intent. Burns aimed at site preparation are conducted in early fall, while silviculture burns are conducted at specific times during the growing season. Burns aimed at hazard reduction may be scheduled later in the season. After burners are given priority according to their objectives, the daily allocation can be filled by randomly drawing from the pool of remaining likely burners.

The next step is to estimate prescribed burn emissions from the selected burn plots. The BlueSky modeling framework can be used for this purpose. The most recent NFDRS maps or fuel information derived from satellites can be used to determine the fuel loads. In the future, permit databases like GFC's can be expanded with information on the stand, such as its composition, age, and condition. This information can then be used in vegetation dynamics models[48] to estimate the changes in fuel loads over time. Fuel consumption can be estimated using CONSUME. Finally, emission factors from a recently compiled nationwide database[49] or the Fire Emission Production Simulator[50] can be applied to the amount of fuels consumed in order to estimate total emissions.

The improved forecast can be used as part of the prescribed burn permitting system for dynamic air quality management. The benefit of such a system is that instead of a blanket burning ban, such as the one imposed in Georgia during the ozone season, burns could be banned only on days when it is imminent that air quality would not meet the standards. Alternatively, burns can be selectively allowed on days when air quality standards likely would be met. The modeling technology exists for calculating the increment of pollutant concentrations at downwind receptors due to emissions from specific sources.[51] It is feasible to use this technology to discern fires from other emissions sources, such as power plants, industries, and transportation, and forecast the amount of fire emissions that can be allowed without exceeding air quality standards for a given day's meteorological capacity to assimilate air pollutants.

The allowable amount of fire emissions can be turned into more useful information for air quality conscious prescribed burn management, such as locations and sizes of burns that can be permitted. To achieve this, the inverse of the emission estimation model described above is needed. The inverse model would start with the emissions and calculate the amount of fuels that would lead to those emissions when consumed by fire. The calculation can be performed on a district- or county-level spatial resolution. The list of likely-to-be-burned plots can then be searched by looking at their estimated fuel loads to fill the allowable emission quotas for each county. Finally, the land managers of the selected plots can be called upon to burn on a given day. Such a dynamic system can significantly increase the capacity of land management by prescribed burns, while also maintaining acceptable air quality.

Summary

Wildfires are intensifying and increasing in frequency as a result of global climate change. At the same time, dependence on prescribed burns is growing both for ecosystem management and hazard reduction purposes. Meanwhile, air quality standards are tightening and other emission sources such as electricity generation and transportation are being heavily controlled. These dynamics will soon leave fire emissions as the major source of air pollution in many areas of the United States. The increasing demand for prescribed burning, combined with increased air quality pressure due to tighter regulatory constraints, necessitates management approaches that require significantly improved fire impact forecasting capability.

Recently, there has been a notable increase in the use of Eulerian CTMs for air quality impact forecasting. Despite significant strides in model development, limitations remain. One limitation is the heavy computational needs imposed by high grid resolutions needed to adequately track fire plumes. Another limitation is the lack of rapid fire emission forecasting capability. Typical fire emissions used in regulatory modeling are too inaccurate for reliable air quality forecasting. The averaging processes involved in developing typical fire inventories spread the fires in space and increase their frequency without considering the weather conditions.

Satellite retrievals, after calibration with ground-based data, can be used to estimate biomass burning emissions for forecasting the impacts of wildfires. Prescribed burns, on the other hand, are of short duration and smaller size, which makes them more difficult to detect with satellites. A new approach is needed to forecast the impacts of prescribed burns. One is proposed here to forecast burn activity based on weather and past burning patterns in well-managed tracts. **em**

Note: For a complete list of references associated with this article, please refer to the online version published at www.awma.org/em.

References

1. Wotawa, G.; Trainer, M. The Influence of Canadian Forest Fires on Pollutant Concentrations in the United States; *Science* **2000**, *288* (5464), 324-328.
2. Kochi, I.; Donovan, G.H.; Champ, P.A.; Loomis, J.B. The economic cost of adverse health effects from wildfire-smoke exposure: A review; *Int. J. Wildland Fire* **2010**, *19* (7), 803-817.
3. Spracklen, D.V.; Logan, J.A.; Mickley, L.J.; Park, R.J.; Yevich, R.; Westerling, A.L.; Jaffe, D.A. Wildfires drive interannual variability of organic carbon aerosol in the western U.S. in summer; *Geophys. Res. Letts.* **2007**, *34* (16), L16816.
4. Flannigan, M.D.; Logan, K.A.; Amiro, B.D.; Skinner, W.R.; Stocks, B.J. Future Area Burned in Canada; *Climatic Change* **2005**, *72* (1-2), 1-16.
5. Rogers, B.M.; Neilson, R.P.; Drapek, R.; Lenihan, J.M.; Wells, J.R.; Bachelet, D.; Law, B.E. Impacts of climate change on fire regimes and carbon stocks of the U.S. Pacific Northwest; *J. Geophys. Res. Biogeosciences* **2011**, *116* (G3), G03037.
6. Westerling, A.L.; Turner, M.G.; Smithwick, E.A. H.; Romme, W.H.; Ryan, M.G. Continued warming could transform Greater Yellowstone fire regimes by mid-21st century; *Proc. Natl. Acad. Sci.* **2011**, *108* (32), 13165-13170.
7. Spracklen, D.V.; Mickley, L.J.; Logan, J.A.; Hudman, R.C.; Yevich, R.; Flannigan, M.D.; Westerling, A.L. Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States; *J. Geophys. Res. Atmospheres* **2009**, *114* (D20), D20301.
8. Tian, D.; Hu, Y.T.; Wang, Y.H.; Boylan, J.W.; Zheng, M.; Russell, A.G. Assessment of biomass burning emissions and their impacts on urban and regional PM2.5: A Georgia case study; *Environ. Sci. Technol.* **2009**, *43* (2), 299-305.
9. *NIFC Wildland Fire Summary and Statistics Annual Report 2012*; National Interagency Coordination Center, 2013.
10. Wade, D.D.; Brock, B.L.; Brose, P.H.; Grace, J.B.; Hoch, G.A.; Patterson, W.A., III. Chapter 4:53-96, Fire in eastern ecosystems. In: Brown, J.K.; Smith, J.K., Eds. *Wildland fire in ecosystems: Effects of fire on flora*; Gen. Tech. Rep. RMRS-GTR-42- Vol. 2; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Ogden, UT, 2000.
11. Dozier, A. Personal Communication. Georgia Forestry Commission: March 17, 2011.
12. Lee, S.; Russell, A.G.; Baumann, K. Source apportionment of fine particulate matter in the southeastern United States; *J. Air & Waste Manage. Assoc.* **2007**, *57*, 1123-1135; doi:10.3155/1047-3289.57.9.1123.
13. Lee, S.; Baumann, K.; Schauer, J.J.; Sheesley, R.J.; Naeher, L.P.; Meinardi, S.; Blake, D.R.; Edgerton, E.S.; Russell, A.G.; Clements, M. Gaseous and Particulate Emissions from Prescribed Burning in Georgia; *Environ. Sci. Technol.* **2005**, *39*, 9049-9056.
14. Hu, Y.; Odman, M.T.; Chang, M.E.; Jackson, W.; Lee, S.; Edgerton, E.S.; Baumann, K.; Russell, A.G. Simulation of Air Quality Impacts from Prescribed Fires on an Urban Area; *Environ. Sci. Technol.* **2008**, *42* (10), 3676-3682; doi:10.1021/es071703k.
15. Zeng, T.; Wang, Y.; Yoshida, Y.; Tian, D.; Russell, A.G.; Barnard, W.R. Impacts of Prescribed Fires on Air Quality over the Southeastern United States in Spring Based on Modeling and Ground/Satellite Measurements; *Environ. Sci. Technol.* **2008**, *42* (22), 8401-8406.
16. Lee, S.; Kim, H.K.; Yan, B.; Cobb, C.E.; Hennigan, C.; Nichols, S.; Chamber, M.; Edgerton, E.S.; Jansen, J.J.; Hu, Y.; Zheng, M.; Weber, R.J.; Russell, A.G. Diagnosis of Aged Prescribed Burning Plumes Impacting an Urban Area; *Environ. Sci. Technol.* **2008**, *42* (5), 1438-1444; doi:10.1021/es7023059.
17. Coen, J.L.; Cameron, M.; Michalakes, J.; Patton, E.G.; Riggan, P.J.; Yedinak, K.M. WRF-Fire: Coupled Weather–Wildland Fire Modeling with the Weather Research and Forecasting Model; *J. Appl. Meteorol. Climatol.* **2012**, *52* (1), 16-38.
18. Ottmar, R.; Vihnanek, R.; Mathey, J. *Stereo photo series for quantifying natural fuels. Volume VIa: sand hill, sand pine scrub, and hardwood with white pine types in the Southeast United States with supplemental sites for Volume VI*; Vol. PMS 838; National Wildfire Coordinating Group, National Interagency Fire Center: Boise, ID, 2003; p. 78.
19. Larkin, N.K.; O'Neill, S.M.; Solomon, R.; Raffuse, S.; Strand, T.; Sullivan, D.C.; Krull, C.; Rorig, M.; Peterson, J.; Ferguson, S.A. The BlueSky smoke modeling framework; *Int. J. Wildland Fire* **2009**, *18* (8), 906-920.
20. Prichard, S.J.; Ottmar, R.D.; Anderson, G.K. *Consume 3.0 User's Guide*; United States Department of Agriculture Forest Service, Pacific Northwest Research Station: Seattle, WA, 2005.

21. Lavdas, L.G.; Jackson, W.A.; Harms, M.F.; Amer Meteorol, S.O.C. VSMOKE—A forestry smoke dispersion algorithm with GIS interface. In *Proceedings of the 22nd Conference on Agricultural & Forest Meteorology with Symposium on Fire & Forest Meteorology/12th Conference on Biometeorology & Aerobiology 1996*; pp 292-295.
22. Riebau, A.R.; Fox, D.G.; Sestak, M.L.; Dailey, B.; Archer, S.F. Simple approach smoke estimation model; *Atmos. Environ.* **1988**, *22* (4), 783-788.
23. Henderson, S.B.; Ichoku, C.; Burkholder, B.J.; Brauer, M.; Jackson, P.L. The validity and utility of MODIS data for simple estimation of area burned and aerosols emitted by wildfire events; *Int. J. Wildland Fire* **2010**, *19* (7), 844-852.
24. Jain, R.; Vaughan, J.; Kyle, H.; Ramosa, C.; Clalborn, C.; Maarten, S.; Schaaf, M.; Lamb, B. Development of the ClearSky smoke dispersion forecast system for agricultural field burning in the Pacific Northwest; *Atmos. Environ.* **2007**, *41* (32), 6745-6761.
25. Rolph, G.D.; Draxler, R.R.; Stein, A.F.; Taylor, A.; Ruminski, M.G.; Kondragunta, S.; Zeng, J.; Huang, H.C.; Manikin, G.; McQueen, J.T.; Davidson, P.M. Description and verification of the NOAA Smoke Forecasting System: The 2007 fire season; *Weather Forecast* **2009**, *24* (2), 361-378.
26. Warneke, C.; de Gouw, J.A.; Stohl, A.; Cooper, O.R.; Goldan, P.D.; Kuster, W.C.; Holloway, J.S.; Williams, E.J.; Lerner, B.M.; McKeen, S.A.; Trainer, M.; Fehsenfeld, F.C.; Atlas, E.L.; Donnelly, S.G.; Stroud, V.; Lueb, A.; Kato, S. Biomass burning and anthropogenic sources of CO over New England in the summer 2004; *J. Geophys. Res. Atmospheres* **2006**, *111* (D23).
27. Lapina, K.; Honrath, R.E.; Owen, R.C.; Val Martín, M.; Hyer, E.J.; Fialho, P. Late summer changes in burning conditions in the boreal regions and their implications for NOx and CO emissions from boreal fires; *J. Geophys. Res. Atmospheres* **2008**, *113* (D11), D11304.
28. Achtemeier, G.L.; Goodrick, S.A.; Liu, Y.; Garcia-Menendez, F.; Hu, Y.; Odman, M.T. Modeling Smoke Plume-Rise and Dispersion from Southern United States Prescribed Burns with Daysmoke; *Atmosphere* **2011**, *2* (3), 358-388.
29. Rao, S.T.; Galmarini, S.; Puckett, K. Air Quality Model Evaluation International Initiative (AQMEII): Advancing the State of the Science in Regional Photochemical Modeling and Its Applications; *Bull. Am. Meteorol. Soc.* **2010**, *92* (1), 23-30.
30. Yang, E.S.; Christopher, S.A.; Kondragunta, S.; Zhang, X.Y. Use of hourly Geostationary Operational Environmental Satellite (GOES) fire emissions in a Community Multiscale Air Quality (CMAQ) model for improving surface particulate matter predictions; *J. Geophys. Res.* **2011**, *116* (D04), D0403.
31. Strand, T.M.; Larkin, N.; Craig, K.J.; Raffuse, S.; Sullivan, D.; Solomon, R.; Rorig, M.; Wheeler, N.; Pryden, D. Analyses of BlueSky Gateway PM2.5 predictions during the 2007 southern and 2008 northern California fires; *J. Geophys. Res.* **2012**, *117* (D17).
32. Garcia-Menendez, F.; Hu, Y.; Odman, M.T. Simulating smoke transport from wildland fires with a regional-scale air quality model: Sensitivity to uncertain wind fields; *J. Geophys. Res. Atmospheres* **2013**, *118* (12), 6493-6504.
33. Byun, D.; Schere, K.L. Review of the governing equations, computational algorithms, and other components of the models-3 Community Multiscale Air Quality (CMAQ) modeling system; *Appl. Mech. Rev.* **2006**, *59* (1-6), 51-77.
34. Mason, R.; Zubrow, A.; Eyth, A. *Technical Support Document (TSD) Preparation of Emissions Inventories for the Version 5.0, 2007 Emissions Modeling Platform*; U.S. Environmental Protection Agency, Office of Air and Radiation, Office of Air Quality Planning and Standards, Air Quality Assessment Division, 2012.
35. Hu, Y.T.; Chang, M.E.; Russell, A.G.; Odman, M.T. Using synoptic classification to evaluate an operational air quality forecasting system in Atlanta; *Atmos. Pollut. Res.* **2010**, *1* (4), 280-287.
36. Odman, M.T.; Hu, Y.; Chang, M.E.; Russell, A.G. Forecasting ozone and PM2.5 in southeastern U.S. In *Developments in Environmental Science*; Volume 6; Borrego, C.; Renner, E., Eds. Elsevier Ltd.: 2007; pp 219-288.
37. *MACTEC, Documentation of the Revised 2002 Base Year, Revised 2018, and Initial 2009 Emission Inventories for VISTAS*; Visibility Improvement State and Tribal Association of the Southeast (VISTAS): 2005.
38. Sullivan, D.C.; Raffuse, S.M.; Pryden, D.A.; Craig, K.J.; Reid, S.B.; Wheeler, N.J.M.; Chinkin, L.R.; Larkin, N.K.; Solomon, R.; Strand, T. Development and applications of systems for modeling emissions and smoke from fires: The BlueSky smoke modeling framework and SMARTFIRE. In *Proceedings of the 17th International Emissions Inventory Conference, Portland, OR, June 2-5*, 2008; available online at www.epa.gov/ttn/chief/conferences.html.
39. Wiedinmyer, C.; Akagi, S.K.; Yokelson, R.J.; Emmons, L.K.; Al-Saadi, J.A.; Orlando, J. J.; Soja, A.J. The Fire INventory from NCAR (FINN): A high resolution global model to estimate the emissions from open burning; *Geosci. Mod. Dev.***2011**, *4* (3), 625-641.
40. Zhang, X.; Kondragunta, S.; Ram, J.; Schmidt, C.; Huang, H.-C. Near-real-time global biomass burning emissions product from geostationary satellite constellation; *J. Geophys. Res. Atmospheres* **2012**, *117*, D23203; doi:10.1029/2012JD017812..
41. Wooster, M.J.; Zhukov, B.; Oertel, D. Fire radiative energy for quantitative study of biomass burning: derivation from the BIRD experimental satellite and comparison to MODIS fire products; *Remote Sensing Environ.* **2003**, *86* (1), 83-107.
42. Al-Saadi, J.; Soja, A.; Pierce, R.B.; Szykman, J.; Wiedinmyer, C.; Emmons, L.; Kondragunta, S.; Zhang, X.; Kittaka, C.; Schaack, T.; Bowman, K. Intercomparison of near-real-time biomass burning emissions estimates constrained by satellite fire data; *J. Appl. Remote Sensing* **2008**, *2*; doi:10.1117/1.2948785.
43. Wooster, M.J. Small-scale experimental testing of fire radiative energy for quantifying mass combusted in natural vegetation fires; *Geophys. Res. Letts.* **2002**, *29* (21).
44. Wooster, M.J.; Roberts, G.; Perry, G.L.W.; Kaufman, Y.J. Retrieval of biomass combustion rates and totals from fire radiative power observations: FRP derivation and calibration relationships between biomass consumption and fire radiative energy release; *J. Geophys. Res. Atmospheres* **2005**, *110* (D24).
45. Zhang, X.; Kondragunta, S.; Schmidt, C.; Kogan, F. Near-real-time monitoring of biomass burning particulate emissions (PM2.5) across contiguous United States using multiple satellite instruments; *Atmos. Environ.* **2008**, *42* (29), 6959-6972.
46. Akagi, S.K.; Craven, J.S.; Taylor, J.W.; McMeeking, G.R.; Yokelson, R.J.; Burling, I.R.; Urbanski, S.P.; Wold, C.E.; Seinfeld, J.H.; Coe, H.; Alvarado, M.J.; Weise, D.R. Evolution of trace gases and particles emitted by a chaparral fire in California; *Atmos. Chem. Phys.* **2012**, *12* (3), 1397-1421.
47. Achtemeier, G.L. On the formation and persistence of superfog in woodland smoke; *Meteorological Applications* **2009**, *16* (2), 215-225.
48. Beukema, S.J.; Kurz, W.A.; Pinkham, C.B.; Milosheva, K.; Frid, L. *Vegetation Dynamics Development Tool, User's Guide, Version 4.4c*; ESSA Technologies Ltd.: Vancouver, BC, Canada, 2003; p 239.
49. Burling, I.R.; Yokelson, R.J.; Griffith, D.W.T.; Johnson, T.J.; Veres, P.; Roberts, J.M.; Warneke, C.; Urbanski, S.P.; Reardon, J.; Weise, D.R.; Hao, W.M.; de Gouw, J. Laboratory measurements of trace gas emissions from biomass burning of fuel types from the southeastern and southwestern United States; *Atmos. Chem. Phys.* **2010**, *10* (22), 11115-11130.
50. Anderson, G.K.; Sandberg, D.V.; Norheim, R.A. *Fire Emission Production Simulator (FEPS) User's Guide*; U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Corvallis, OR, 2004.
51. Napelenok, S.L.; Cohan, D.S.; Odman, M.T.; Tonse, S. Extension and evaluation of sensitivity analysis capabilities in a photochemical model; *Environ. Mod. Soft.* **2008**, *23* (8), 994-999.